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❑ Production Scheduling at Falcon Die Casting

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Abstract:

Production scheduling is one of the most crucial parts of process manufacturing and for industries to stay competitive in business, scheduling is a key area that needs to be given greater importance. In this case study Falcon die casting company needs to plan production by taking into consideration the demand for the coming 12 weeks. The goal is to fulfil the demand by using least working hours. For this the task is to create an optimal schedule such that the demand is met by paying the least amount for overtime. Also the production schedule has to be feasible enough to perform a routine schedule without disturbing the machine setups. Scheduling is considered as a last stage and labor, facilities and equipment are considered objective functions in it. The process of mathematical modeling and to consider the decision-making implications of their models. Determining the optimal job for machines and workers will be solved by implementing a linear programming method. The final solution will be such that production capacity is adjustable by adding minimum hours for each machine in each working shift. The primary objective of scheduling is to meet demand due date and the secondary one is to minimize total overtime.

Keywords:

Modeling techniques for Production Scheduling, Optimization, Linear Programming, Travelling Salesman Problem, Demand Fulfilment, Gurobi Optimizer.

1. Introduction and Motivation

The optimum utilization of limited resources in an organization allows the production/supply chain manager to make decisions on the best use of limited resources. In this analysis, we are going to use a linear programming method to solve a production scheduling problem in a business that produces different parts in an automobile industry using die casting in order to meet the predicted demands and reduce cost. In order to optimize the production system with the projected demand by FDC, production rates, part set up time subjected to a given set of constraints we are planning to formulate a linear programming model based on the data provided by Falcon die casting. The second part of this project will concentrate on checking the impact of not carrying finished goods to inventory week to week. The team has studied concepts related to production work hours scheduling under Deterministic Systems Analysis Coursework in which we had to study optimization of employee work shifts exposed to various constraints. Major companies like Volkswagen Group, Toyota Group are investing millions of dollars in optimizing their production system and building a robust, resilient supply chain network. This problem statement has huge scope and we would like to work on this and enhance our knowledge in this field.

1.1 Project Charter

Project Description:

The main aim of this project is to develop and optimize Scheduling to be done in a systematic manner along with certainty that the final schedule allocates processing of components for machines in an optimal manner. This project will also focus on testing the effect of not shipping finished products to stock week by week.

Problem Statement:

To use a linear programming approach to solve a production scheduling issue in a company that uses die casting to manufacture various parts in an automotive industry to meet the demand requirements and minimize costs.

Goal Statement:

We intend to formulate a linear programming model based on the data generated by Falcon die casting in order to optimize the production system with the projected demand by FDC, production rates, part set up time subject to a given set of constraints.

-to reduce the production cost by systematically scheduling the production process so that employees don't have to work overtime.

-to meet the projected demand.

-to test the effect of not shipping finished products to stock week by week.

Scope:

The scope of this project is to minimize cost and to meet the required demand by optimizing and scheduling of a production firm.

In Scope:

In this project we will be using concepts related to production work hours scheduling under Deterministic Systems Analysis from our coursework.

Out of Scope: Tools like SAP, Netsuite for solving production scheduling problems.
Assumptions: • The demand beyond week 2 is tentative and subject to change depending on the auto sales. • 'Yielding factor' for every part is estimated to meet the customer quality specifications • Company's long term policy involves not keeping finished goods inventory at the end of the week which limits the production to just that week's demand. • All machines are set up anew each week and the setting up times range from 8 hours to 24 hours.
Constraints: • Maximum working hours for each machine = 120 hours/week • Maximum overtime hours for each machine = 40 hours/week • The yield % for parts 1 to 5 are 60%, 55%, 75%, 65% and 60% respectively.

2. Literature Review

Production scheduling perhaps because of its quantifiable structure with its numerous variables continuous to attract many researchers. There are several reviews on this topic, in this particular section we summarize those that are most relevant to our project. The main aim of this case study is to study and analyze the current available algorithm to predict an optimal solution. This case article focuses on the application of production scheduling at Falcon Die Casting. In 1955, Edward H. Bowman explained a critical evolution of production planning, according to him the methods used for scheduling lacked the basic understanding of constraints. The author hopes that the practitioners will have this paper useful for future study.[1] In 1981, Stephen C Graves briefly discussed production scheduling involving a set of tasks to be performed between both tradeoffs. He classified different problems to review important theoretical developments in case studies. He discussed a significant discrepancy between practice and theory of production scheduling.[2] In 2004, Nafee Rizk, Alain Martel and Sophie D'Amours described an innovative search algorithm for production scheduling which consisted of crossover operators which predetermine production sequence while maintaining mixed integer programming. This search technique can be utilized to solve production scheduling at large dimensions through commercial integer programming.[3] Production scheduling perhaps because of its quantifiable structure with its numerous variables continuous to attract many researchers in 2014 Jalel Ben Hmida, Jim Lee, Xinchun Wang & Fathi Boukadi came up with a continuous manufacturing problem and its solution with quality constraints [4] In 2014 Samuel Moniz, Ana Paula Barbosa-Póvoaa, Jorge Pinho de Sousa presented how simultaneous regular and non-regular production scheduling problems could be solved on virtual platforms with mixed algorithms to derive optimal solutions. Their approach explores the RTN (Resource Task Network) discrete time formulation similar to rolling horizon approach mixed with branching strategies.[5] Production Scheduling in Flexible Manufacturing Systems. This paper proposed a survey over the latest research on the field of production scheduling. This problem is approached with the hybrid algorithms to find an optimal solution in real flexible manufacturing systems. The given solutions are based on the data input for scheduling and manufactured goods.[6] Andrzej Bozek and Frank Werner during 2017 discussed a case of flexible job shop scheduling with Iot streaming and sublot size optimization. They have classified this problem in two steps, firstly they have shortened the makespan value which helps with minimizing quality of the product. Secondly they have used mixed integer programming with constraints-graph programming and have concluded with two different results. This obtained solutions are then compared for the optimal answer.[7] In 2017, Stef Moons, Kartein Ramaekers, An Cris and Yasemin Arda reviewed and discussed about integrating production scheduling and vehicle routing decisions at operational decision level.[8] Apostolos P. Elekidis, Francesc Corominas, and Michael C. Georgiadis in 2019 classified their study on Production Scheduling of Consumer Goods Industries into two different MILP- based decomposition strategies are used to solve this realistic problem. This proposed solution strategy has provided the basis for the development of tools that will allow near-optimal scheduling decisions in Consumer Goods Industries. [9]

3. Model

The model we have constructed deals with meeting all 12 week's demands. We have interpreted the created model based on the output and suggested the corrective measures or options for optimization.

The Mathematical computations are as follow:

Objective Function: Minimize the production hours (regular & overtime) while meeting demand for 12 weeks.

Let, i = parts number (i=1,2,3,4,5) | j = machine number (j=1,2,3,4,5)

Let the cost of production at regular hours be \$100 and for overtime be \$150 (assumed and stated by problem statement).

For mathematical modelling we will define a model for explanation but in actual execution we will be defining different variables.

Let setup time be denoted by S_{ij}.

Yield Rate: Y_i | Demand/Week= d_i | Production Rates = P_{ij}.

Let machine time be denoted by m in regular production and z for overtime production hours. We have constraints like Total Demand = Total Production.

Individual machine production time constraints containing production hours and setup hours.

Machine time constraint like 120 hours/week for each machine and 48 hours/week for overtime.

4. Data

The datasets used for this project are as follows:

1. The projected demand for the auto parts for 12 weeks.

Source: https://pubsonline.informs.org/doi/10.1287/ited.2014.0132cs

Table 1 Projected Demand

Week	Part 1	Part 2	Part 3	Part 4	Part 5
1	3,500	3,000	4,000	4,000	2,800
2	3,000	2,800	4,000	4,300	2,800
3	3,000	2,000	4,000	3,500	3,000
4	3,000	3,000	4,000	3,800	2,800
5	3,000	3,000	4,000	4,000	2,800
6	3,500	2,500	4,000	3,800	2,500
7	3,500	2,500	3,800	4,000	2,500
8	3,300	3,400	3,700	4,200	2,500
9	3,300	3,400	0	4,500	3,000
10	3,200	3,000	0	4,500	3,000
11	4,500	4,000	5,000	5,000	3,800
12	3,000	2,800	4,000	4,300	2,800

Figure 5. Demand Forecast for 12 weeks for all Parts

Assumption: Demand after week 2 is tentative, depends on the sales of the preceding week.

Production rate and part time setups for every machine and respective parts.

Source: https://pubsonline.informs.org/doi/10.1287/ited.2014.0132cs

Table 2 Production Rates (Units/Hour)

	Part 1	Part 2	Part 3	Part 4	Part 5
Machine 1	40			60	
Machine 2	35	25			
Machine 3		30			45
Machine 4		35	50		
Machine 5				60	50
Yield (%)	60	55	75	65	60

Table 3 Part Setup Times (Hours)

	Part 1	Part 2	Part 3	Part 4	Part 5
Machine 1	8			8	
Machine 2	10	8			
Machine 3		10			24
Machine 4		8	12		
Machine 5				8	20

Assumptions: Yielding factor is estimated by the industrial engineers to meet the quality levels and there is no wastage of the metal since the defective parts can be melted and reused.

Limitations: Production of one part can be forced to set up on multiple machines to meet the required demand of the parts eventually resulting in excessive overtime.

5. Numerical Computations and Results:

We have solved the problem using Python and the Gurobi Optimizer, which is a commercial optimization solver for linear programming.

The code is done in following method:

```
# coding: utf-8

# In[40]:


import pandas as pd
import itertools
from gurobipy import *
production = pd.read_excel("base_case_data.xlsx", header = 0, index_col=0, sheet_name = "production")
setup = pd.read_excel("base_case_data.xlsx", header = 0, index_col=0, sheet_name = "setup")
demand = pd.read_excel("base_case_data.xlsx", header = 0, index_col=0, sheet_name = "demand")
```

Figure 1. Importing Data from Excel File

We have used pandas and gurobipy libraries. The data is stored in the excel file (base_case_data.xlsx) having 3 sheets namely production containing production rate data, setup sheet containing setup times per machine for different parts and demand sheet containing the weekly demand for weekly parts demand.

```
# maximum regular working hours per week
regular_hours_machine = {}
for name in machines:
    regular_hours_machine[name] = 120

# maximum overtime hours per week
overtime_hours = {}
for name in machines:
    overtime_hours[name] = 48


# Demand of each part
constraint_left_p_eq = {}
# example {"Part1":{"Machine1_Part1_Production":24, ...}}
for p in parts:
    production_co = {}
    for v in combine_list:
        first = v.split("_")[0]
        second = v.split("_")[1]
        if second ==p:
            production_co[v] = production.loc[first, second]
```

Figure 2. Specifying Working Hours and Demand Constraints

The maximum regular working hours per week is 120 and overtime is 48. We declared the variables for them. The demand data variable is stated and declared as well.

```
# setup time for each machine
setup_time_machine = {}
# example {"Machine1":{"Machine1_Part1_Production":8, ...}}
for m in machines:
    setup_dic = {}
    for v in combine_list:
        first = v.split("_")[0]
        second = v.split("_")[1]
        if first == m:
            setup_dic[v] = setup.loc[first, second]
        else:
            setup_dic[v] = 0
    setup_time_machine[m] = setup_dic


# production time for each machine
production_time_machine = {}
# example {"Machine1":{"Machine1_Part1_Production":24, ...}}
for m in machines:
    production_dic = {}
    for v in combine_list:
        first = v.split("_")[0]
        second = v.split("_")[1]
        if first == m:
            production_dic[v] = 1
        else:
            production_dic[v] = 0
    production_time_machine[m] = production_dic
# production_time_machine
```

Figure 3. Production and setup time for each machine

The setup time and production time for each machine variable are as follows. Here we use the Boolean terminology where if one part is being manufactured it is assigning the value 0 and others 1.

```
obj = quicksum(overtime_production_levels[vp] for vp in combine_list)
m.update()
m.setObjective(obj, GRB.MINIMIZE)
m.update()
m.optimize()
cost = 0
regular_hours = 0
for variable in m.getVars():
    if variable.x != 0:
        name = variable.varName
        n1 = name.split("[")[0]
        n2 = name.split("[")[-1][:-1]
        if n1 == "setup":
            value = setup_cost[n2]*variable.x
            cost += setup_cost[n2]*variable.x*100
            regular_hours += setup_cost[n2]*variable.x
        elif n1 == "regular":
            value = variable.x
            cost += 100*variable.x
            regular_hours += variable.x
        else:
            value = variable.x
            cost += 150*variable.x
        print('%s %g' % (variable.varName, value))

print('Obj: %g' % m.ObjVal)
print('total cost1: %g' % cost)
print("regular hours: %g" % regular_hours)
m.reset()
```

Figure 4. Final Code for Optimal Solution

We deploy the Gurobi Optimizer and get the output for the 12 weeks production schedule.

To obtain the results, Gurobi Optimizer version 9.1.1 was used. The data and code from python programming were fed to the Gurobi model.

Following are the results for demand for week 1:

The initial model consists of 10 rows, 75 columns and 60 non-zeros.

Model has 5 quadratic constraints.

Variable types are: 50 continuous variables, 25 integer variables (binary)

Regular production time (hours) results:

	Part 1	Part 2	Part 3	Part 4	Part 5	Total
Machine1	1.4359			102.56		104
Machine2	110					110
Machine3		110				110
Machine4			100			100
Machine5					93.33	93.33

Table 1. Regular Production Hrs for week 1

Overtime production time (hours) results:

	Part 1	Part 2	Part 3	Part 4	Part 5	Total
Machine1	48					48
Machine2	0.168					0.168
Machine3		23.596				23.596
Machine4		41.333	6.67			48
Machine5						-

Table 2. Overtime Production Hrs for week 1

Annual cost for week 1: $77298 and total regular hours: 593.33

Similarly, the above procedure is followed for the next 12 weeks.

6. Summary and Conclusions

The study dealt with defining a mathematical model for scheduling the production process to minimize the production costs and production work hours. In addition, we formulated the model and specified respective objective function, constraints and decision variables. Lastly, we created python code for LP optimization and fed the model to the Gurobi Optimizer version 9.1.1.

Week 11 results are not feasible since the constraints are not satisfied. The results and optimal solutions for the total production hours (regular and overtime) and costs are evident from the snapshots provided earlier.

It is impossible to cover all demand for week 11 due to the time constraints.

If carrying inventory was allowed, then this would solve the problem of Week 11's unmet demand.

Q) What considerations need to be made in order to consider routine maintenance that doesn't disturb machines setup?

One thing that can be done is if there is no available time during the week (due to continuous production), routine maintenance can be done during weekends and there won't be any interruption in the production during the weekdays. Also, not all machines use overtime hours during the weekends.

7. List of Contributions

No.	Team Member Name	Contribution
1	Aniket Amar Thopte	Mathematical modeling and code, literature review and presentation
2	Brian Joseph	Numerical computation and optimizing, literature review, presentation
3	Shivraj Bhandigare	Optimizing, calculations, literature review, conclusion and presentation

8. List of Supporting Files

No.	File Name	Description
1	Python Code File Team3_CaseStudy1_ Code file.ipynb	The python code to run the integer programming problem in Gurobi Optimizer.
2	Excel data file Team3_CaseStudy1_ base_case_data.xlsx	The modified data file including yield percentages used for the model
3	Results (Excel file) Team3_CaseStudy1_ Final Results.xlsx	Results obtained for 12 weeks of production

9. List of Abbreviations

TSP: Traveling Salesman Problem

FDC: Falcon Die Casting

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